2007

Observation-model compatibility in coastal data assimilation: filtering and optimal spectral decomposition (OSD)

Chu, P.C.

Observation-Model Compatibility in Coastal Data Assimilation

-Filtering & Optimal Spectral Decomposition -

Peter C. Chu

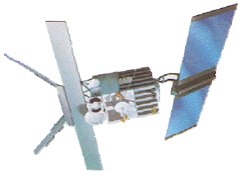
Naval Postgraduate School

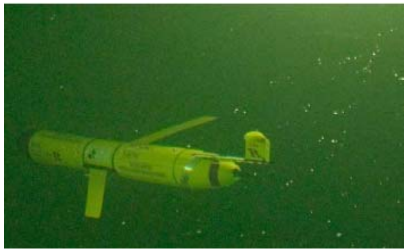
and Other Contributors

Workshop for Environmental Modeling of California Central Coast
MBARI, Moss Landing, California, 15-16 August 2007

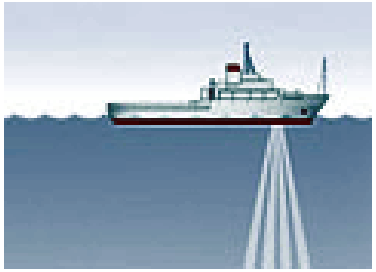
Other Contributors

- Leonid .M. Ivanov, Tatanya Margolina, Chenwu Fan, NPS
- Oleg Melnichenko, University of Hawaii
- N.C. Wells, SOC, UK
- Charles Sun, NOAA/NODC
- George Galanis, George Kallos, University of Athens, Greece





How can we effectively use observational ocean data to represent and to model/predict the ocean state?



Outline

- (1) Model-Data Compatibility
- (2) Filtering Observational Data
- (3) Optimal Spectral Decomposition

  (Chu et al., 2003 a, b JTECH)

  – ARGO Data: Baroclinic Rossby Waves in Tropical Atlantic (Chu et al. JGR 2007)
  – Surface Drifting Buoy Data: Synoptic Current Reversals on the Texas-Louisiana Continental Shelf (Chu et al. 2005 JPO)

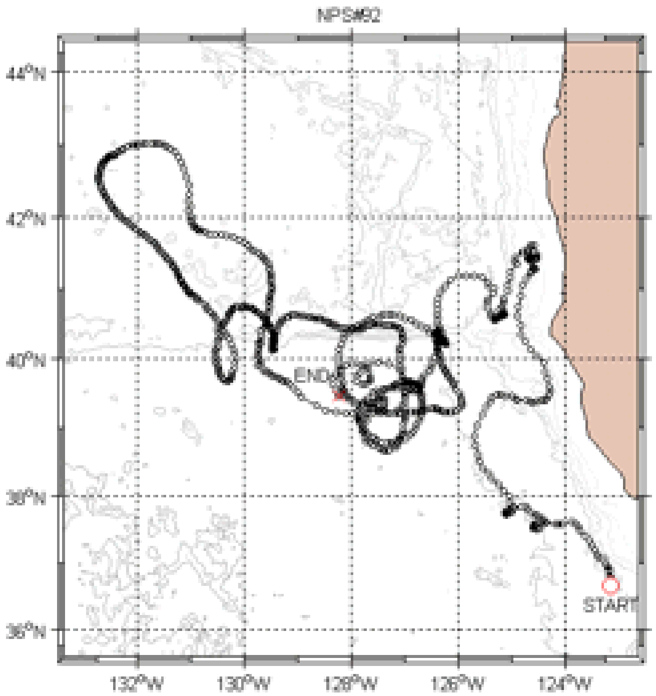
Part-1

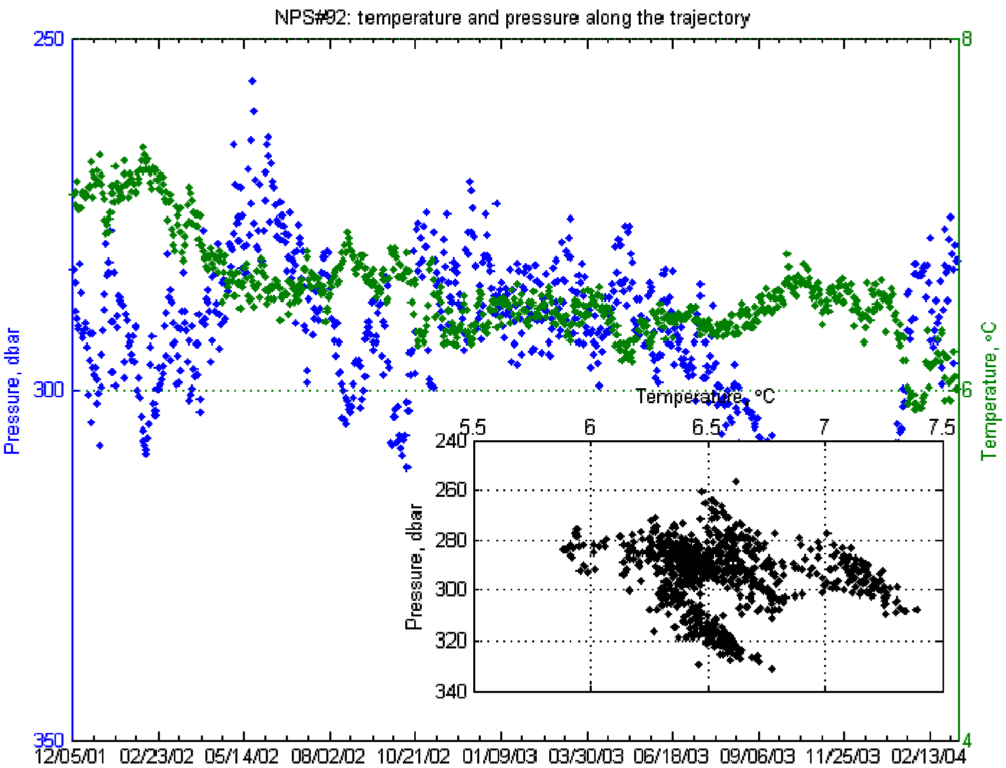
Model-Data Compatibility

Difference between modeled and observed data

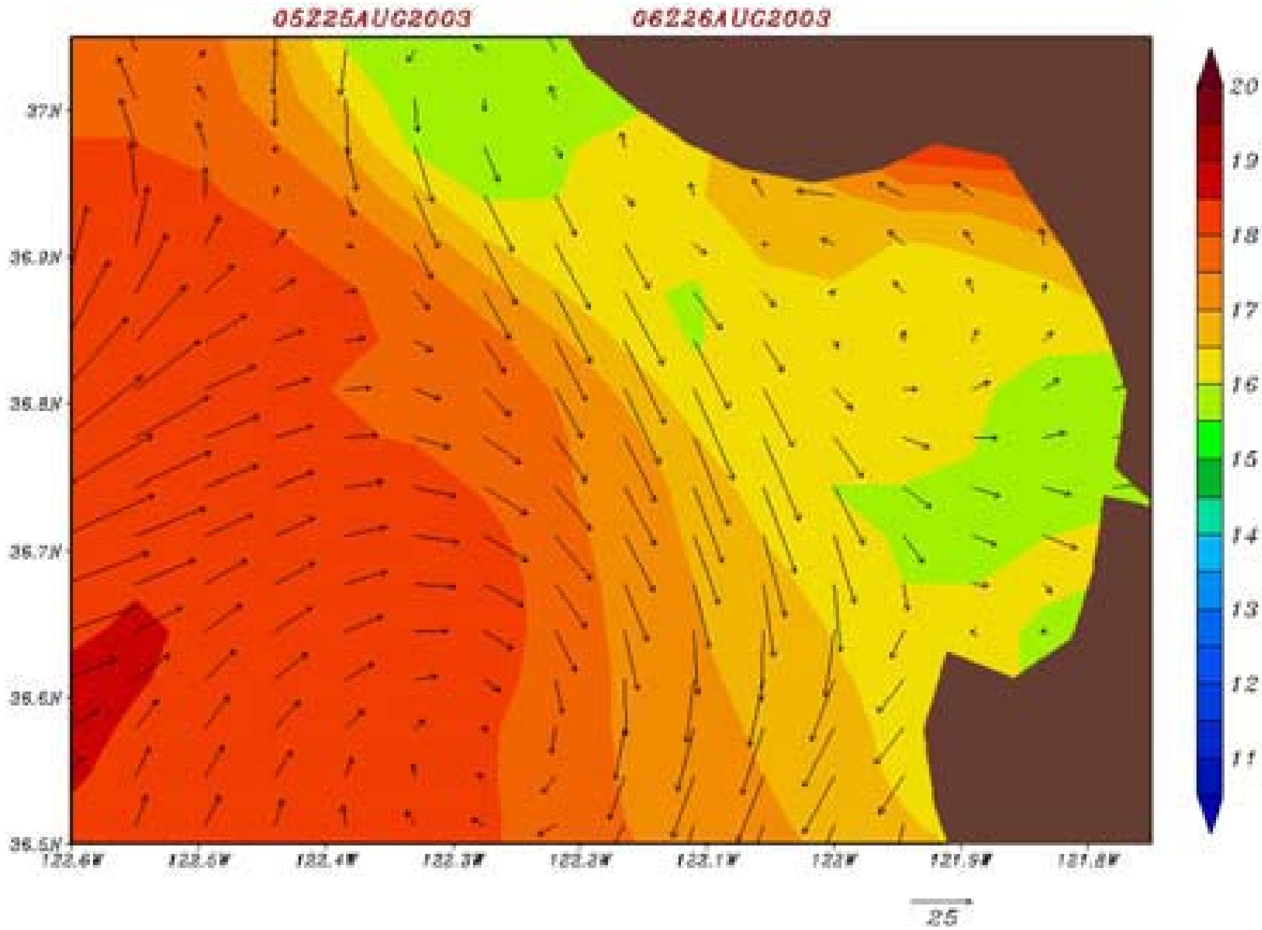
- Model
  - Regular in (t, x, y, z)
  - Representing mean value of a grid cell
- Observation
  - Irregular in (t, x, y, z) usually noisy and sparse
  - Representing value at the observational point

Example: RAFOS Floats (NPS#92) in Monterey Bay (Collins' website)





NCOM Model Data (Hong et al. 2005)

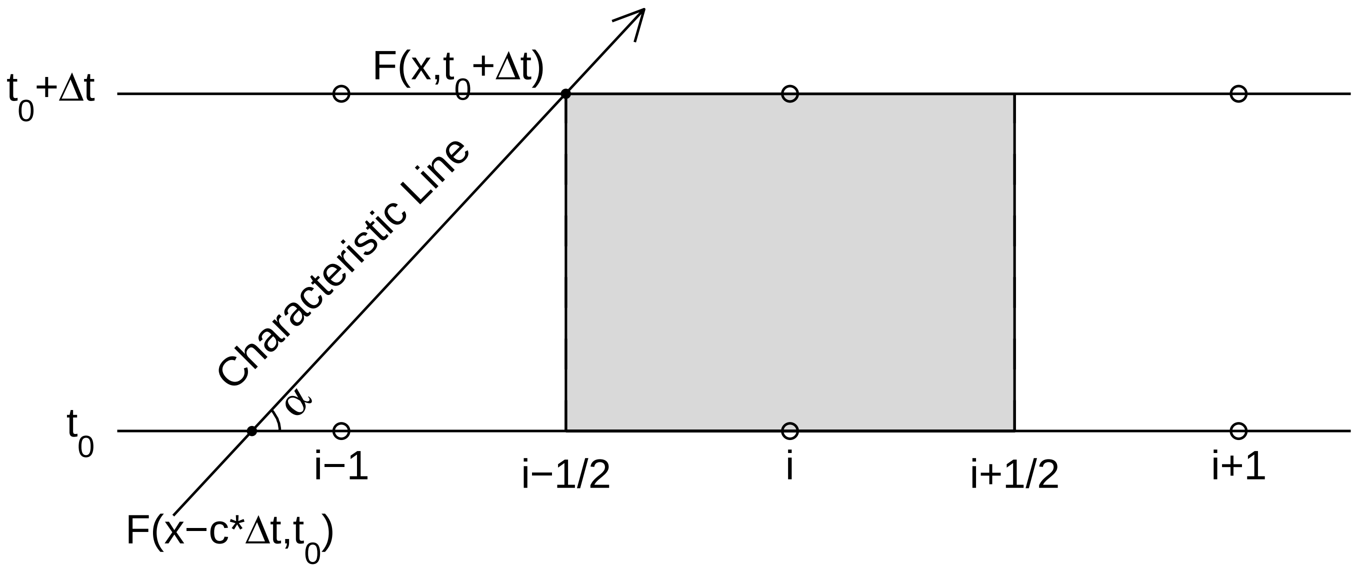


Advection-Diffusion Equation

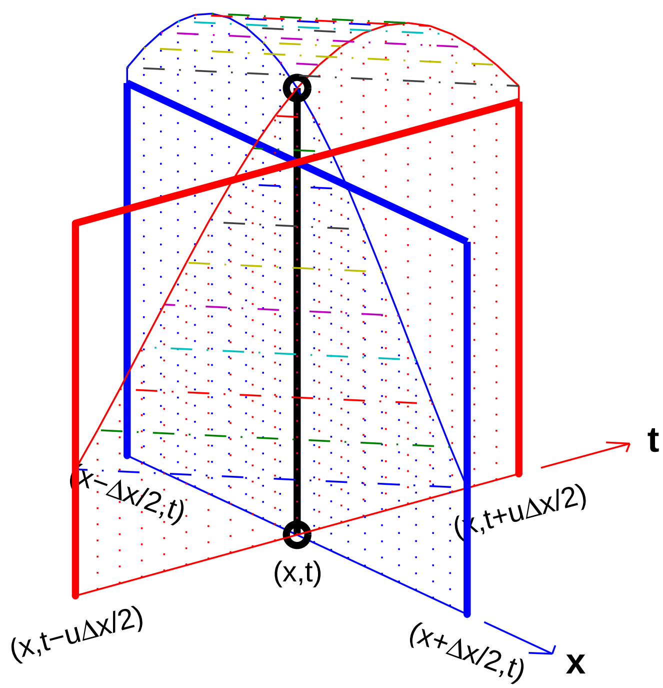
$$\frac{\partial \Phi}{\partial t} + \nabla \bullet (\mathbf{V}\Phi) = \nabla \bullet (\kappa \nabla \Phi) + S\,.$$

$$\frac{\tilde{\Phi}^{n+1}_{i,j,k} - \tilde{\Phi}^{n}_{i,j,k}}{\Delta t} = \frac{\overline{\langle F \rangle}_{i+\frac{1}{2},j,k} - \overline{\langle F \rangle}_{i-\frac{1}{2},j,k}}{\Delta x} + \frac{\overline{\langle G \rangle}_{i,j+\frac{1}{2},k} - \overline{\langle G \rangle}_{i,j-\frac{1}{2},k}}{\Delta y} + \frac{\overline{\langle H \rangle}_{i,j,k+\frac{1}{2}} - \overline{\langle H \rangle}_{i,j,k-\frac{1}{2}}}{\Delta z} + \hat{S}_{i,j,k}\,,$$

Characteristic Line



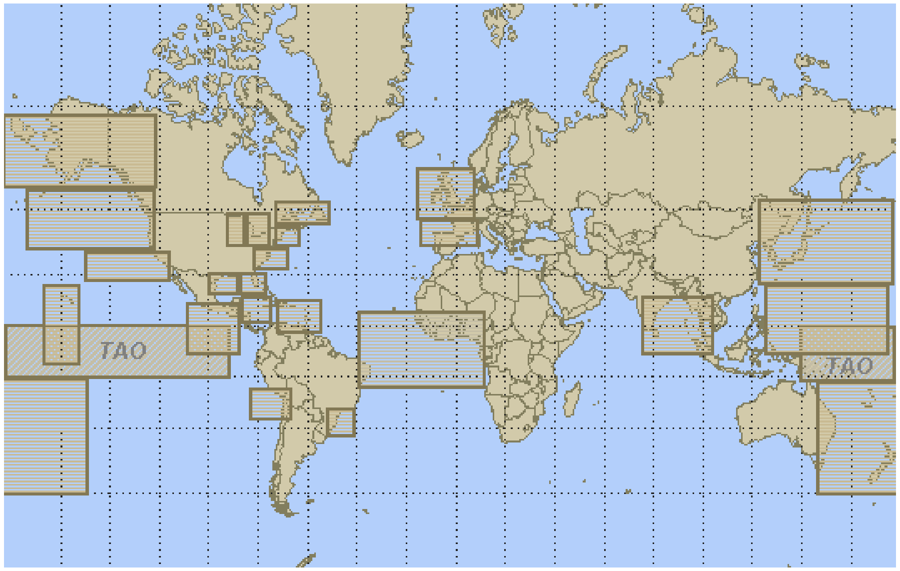
Modeled-Observational Data Difference at the same location



- (1) Observation → along the red curve
- (2) Model → spatial mean (upper blue line)
- (3) Temporal mean of observation ←→ Model

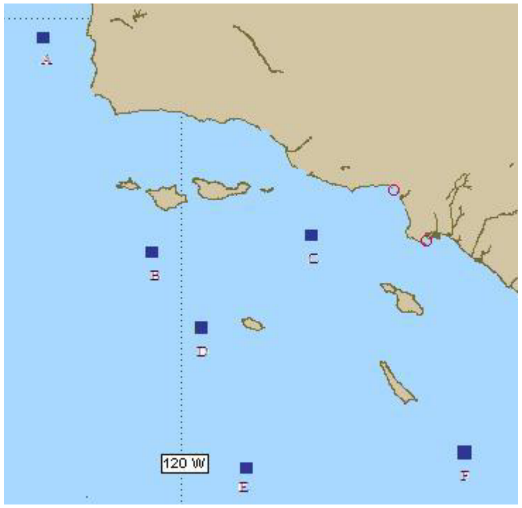
NOAA Buoy Data Center ←→WAM

significant wave height



WAM-4 model
(Galanis et al., 2006)

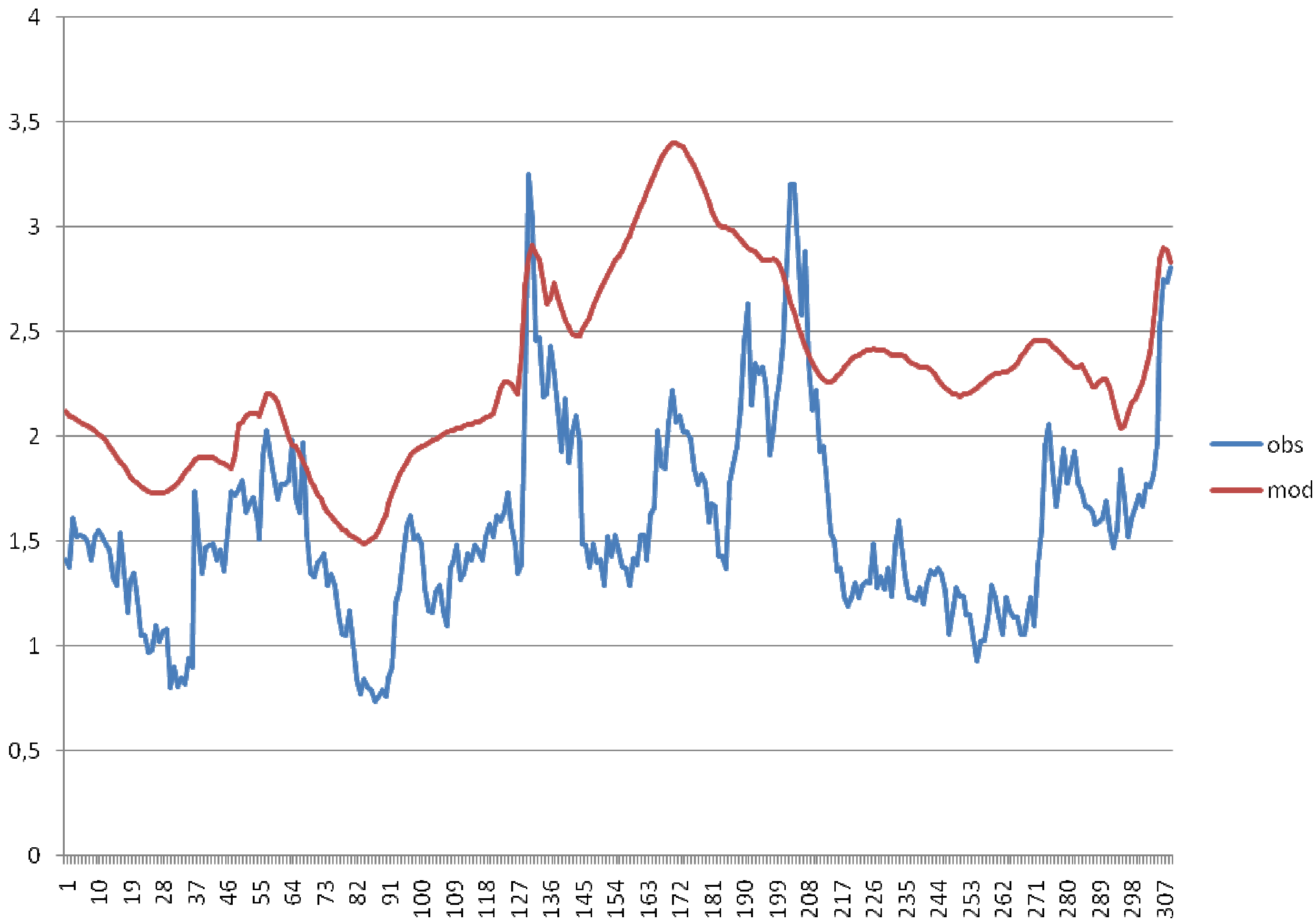
Near California Coast



WAM -4

- (1) Integrating on 30 frequencies and 24 directions.
- (2) First integration frequency → 0.0417 Hz
- (3) Time step → 300 seconds
- (4) Spatial grid → 0.5º x0.5º
- (5) Wind input (10 m) → NCEP/GFS 0.5º x0.5º

Observational and WAM Modeled Data



Part-2 Data Filtering

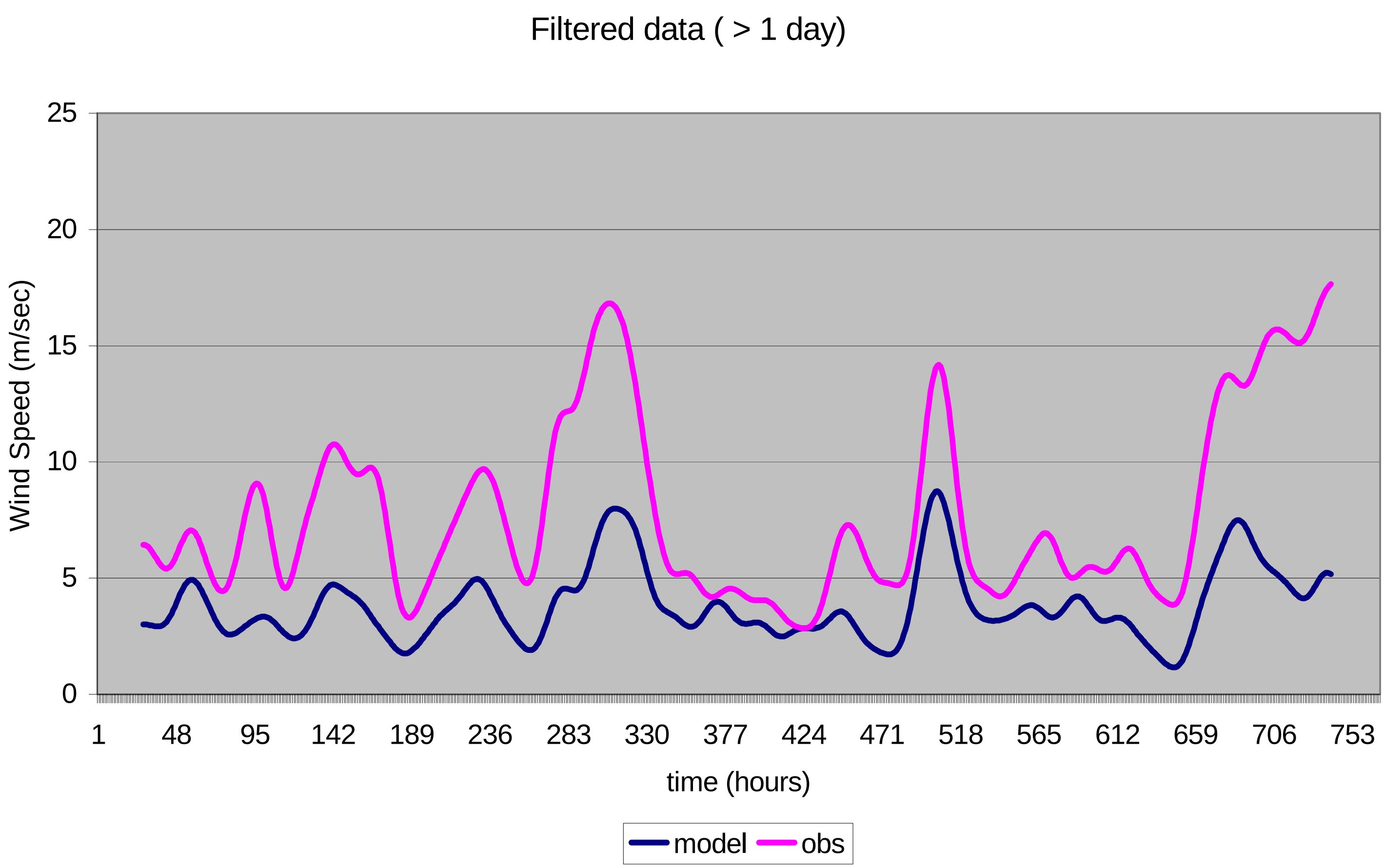
Kolmogorov-Zurbenko (KZ) Filter

KZ Filter

- Original Data x_i^0
- First Iteration $$x_i^1 = \frac{1}{2q+1}\sum_{j=-q}^{q} x_{i+j}^0$$
- Second Iteration $$x_i^2 = \frac{1}{2q+1}\sum_{j=-q}^{q} x_{i+j}^1 ,$$
- Number of Iteration (N) $$(2q+1)\cdot\sqrt{N} \le P$$
- P → Time Steps

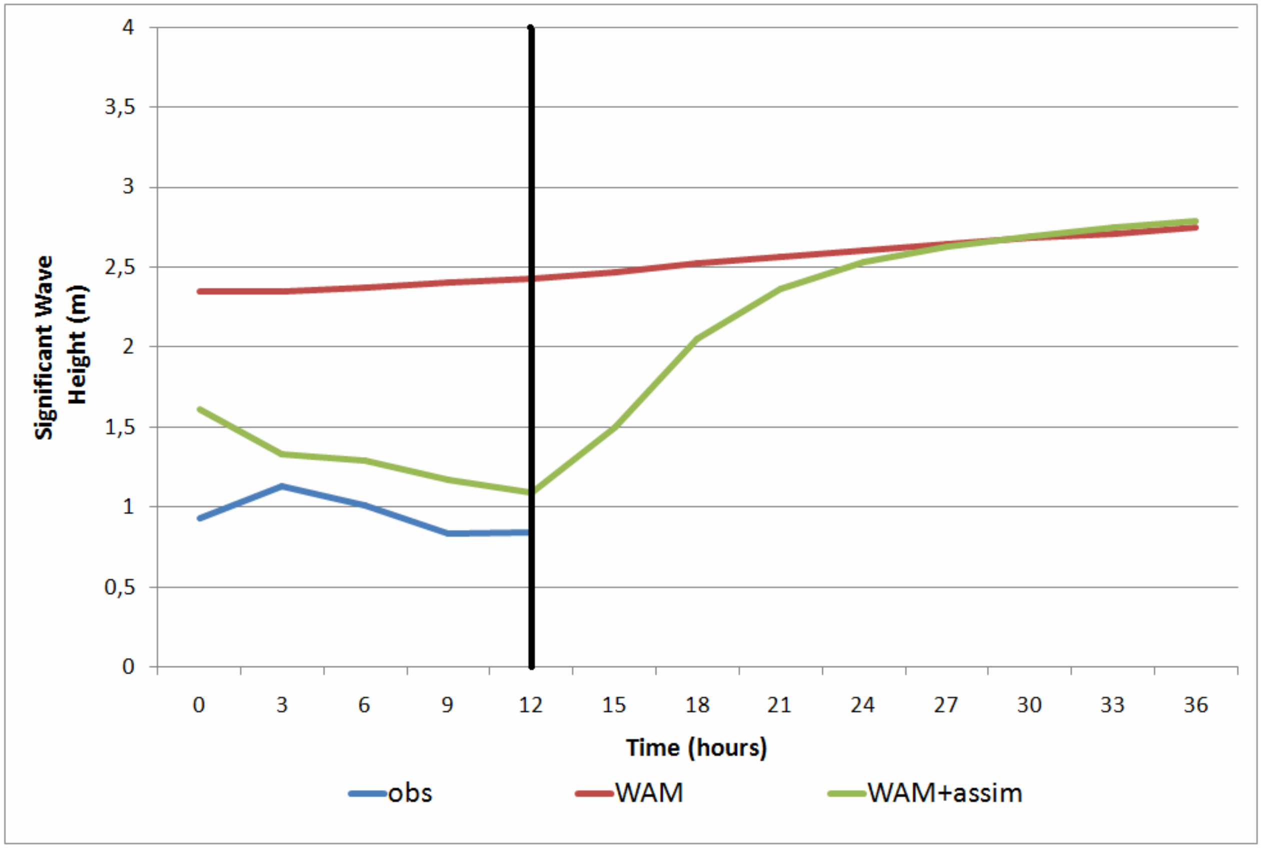
- Appropriate selection of the parameters (N, P, q) leads to smoothed time series of observational and modeled data

Observations vs Forecasts



Daily variability has been removed.
The systematic error has not been affected.

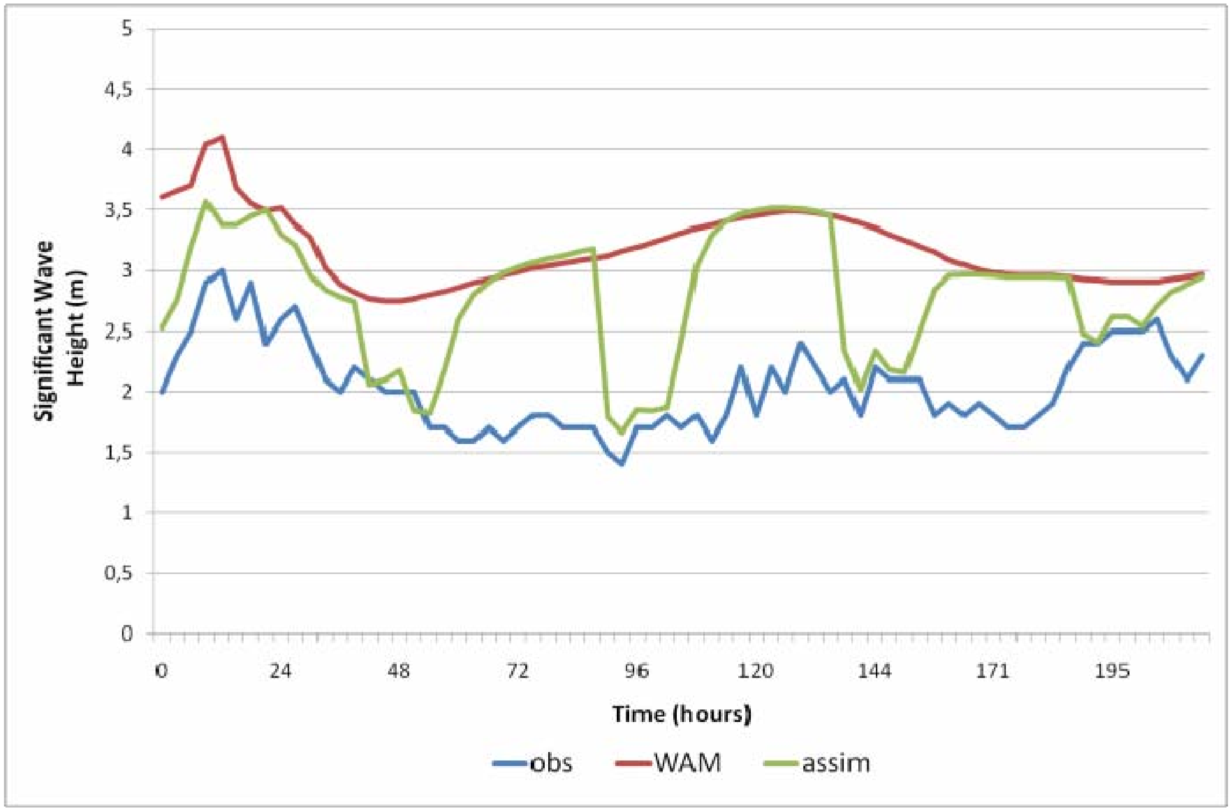
Data Assimilation Window (12 hrs)



Assimilating SWH for 12 hrs and running the model for 24 hrs

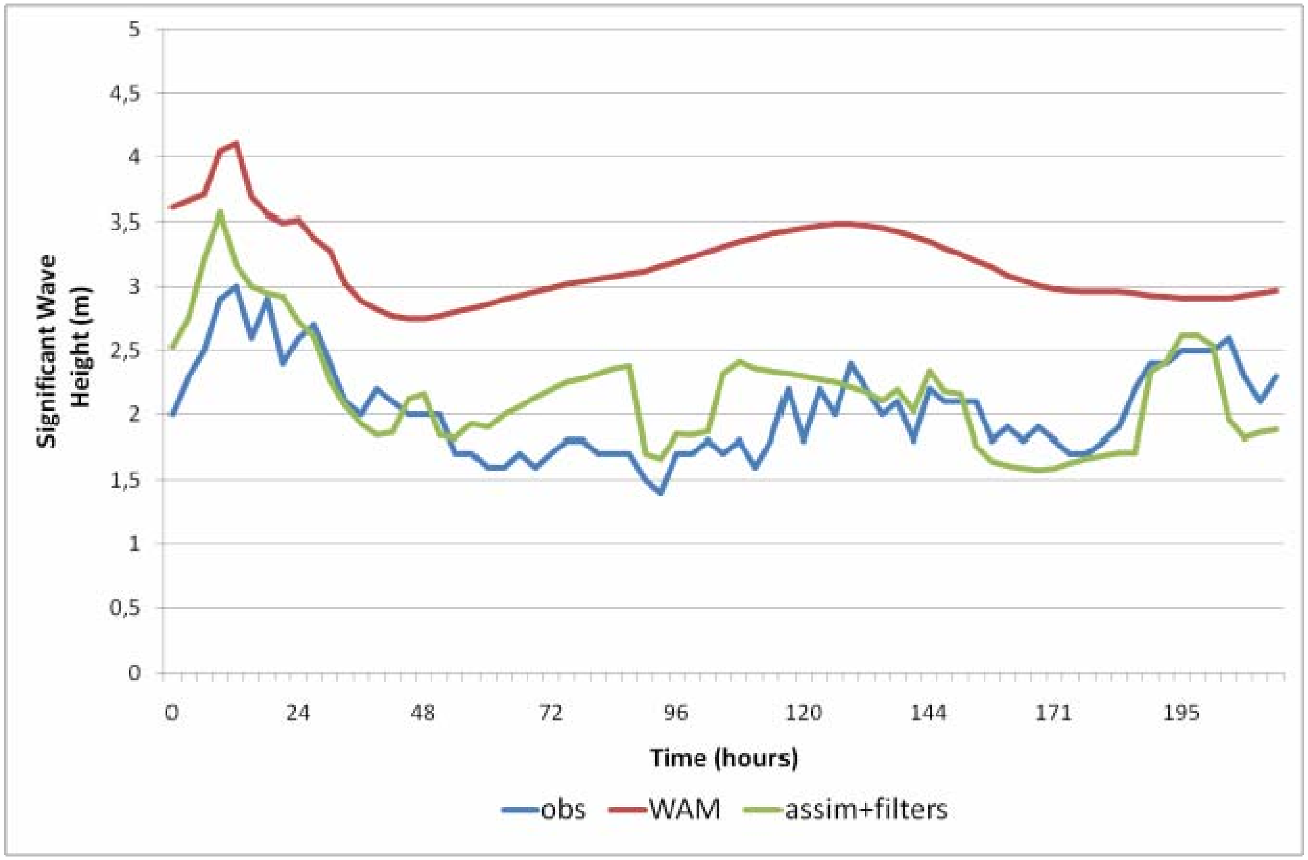
Assimilation → Kalman Filter

Model with data assimilation (Kalman Filter) and no KZ (Buoy- D)



Data (Significant Wave Height) input → Every hours

Model with data assimilation (Kalman Filter) and KZ (Buoy- D)



Impact of Data Assimilation and Filtering

WAM-no assimilation and KZ filtering
WAM2 –assimilation and no KZ filtering
WAM3 – Assimilation and KZ-filtering

	Buoy A			Buoy B			Buoy C		
	WAM	WAM2	WAM3	WAM	WAM2	WAM3	WAM	WAM2	WAM3
Bias	0.51	0.21	0.02	0.39	0.08	-0.19	0.99	0.72	0.33
RMSE	0.70	0.55	0.46	0.64	0.49	0.47	1.10	0.89	0.55
Nbias	0.42	0.28	0.21	0.33	0.22	0.17	1.05	0.73	0.40

	Buoy D			Buoy E			Buoy F		
	WAM	WAM2	WAM3	WAM	WAM2	WAM3	WAM	WAM2	WAM3
Bias	0.68	0.39	0.10	0.62	0.27	-0.02	0.88	0.44	0.02
RMSE	0.80	0.60	0.38	0.79	0.56	0.42	0.96	0.65	0.27
Nbias	0.44	0.27	0.16	0.43	0.24	0.15	0.74	0.38	0.15

Part-3

Optimal Spectral Decomposition

Spectral Decomposition

$$
\begin{aligned}
u_{KM} &= \sum_{k=1}^{K} a_k(z,t^\circ)\frac{\partial \Psi_k(x,y,z,\kappa^\circ)}{\partial y} + \sum_{m=1}^{M} b_m(z,t^\circ)\frac{\partial \Phi_m(x,y,z)}{\partial x}, \\
v_{KM} &= -\sum_{k=1}^{K} a_k(z,t^\circ)\frac{\partial \Psi_k(x,y,z,\kappa^\circ)}{\partial x} + \sum_{m=1}^{M} b_m(z,t^\circ)\frac{\partial \Phi_m(x,y,z)}{\partial y}
\end{aligned}
$$

Basis Functions (Open Boundaries)

(Chu et al., 2003 a,b JTECH)

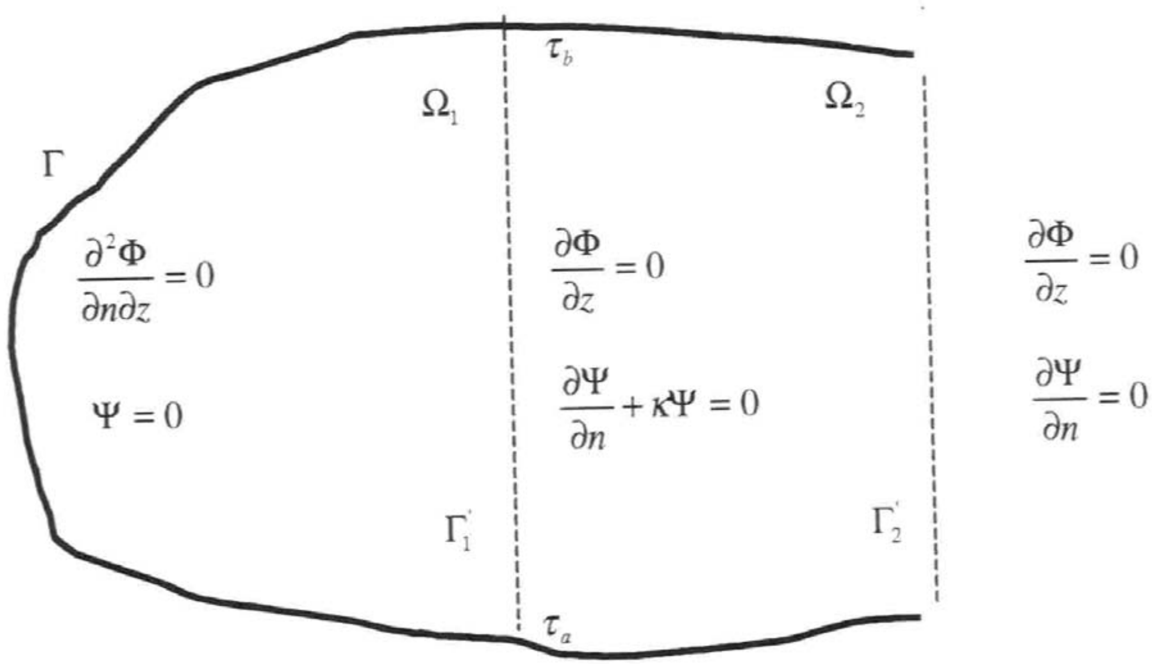
$$\triangle\Psi_k = -\lambda_k \Psi_k,$$

$$\triangle\Phi_m = -\mu_m \Phi_m,$$

$$\Psi_k|_\Gamma = 0, \quad \frac{\partial\Phi_m}{\partial n}|_\Gamma = 0,$$

$$\left[\frac{\partial\Psi_k}{\partial n} + \kappa(\tau)\Psi_k\right]|_{\Gamma_1'} = 0, \quad \Phi_m|_{\Gamma_1'} = 0,$$

Boundary Conditions



Benefit of Using OSD

- Ocean Topographic Configuration →

  Basis Functions (Pre-Determined)

Vapnik (1983) Cost Function →Optimal Mode Truncation

$$J(a_{1,\ldots,}a_K, b_{1,\ldots,}b_M, \kappa, P) = \frac{1}{2}\left(\left\|u_p^{obs} - u_{KM}\right\|_P^2 + \left\|v_p^{obs} - v_{KM}\right\|_P^2\right) \to \min,$$

$$J_{emp} = J(a_{1,\ldots,}a_{K,}b_{1,\ldots,}b_M, \kappa, P).$$

$$\mathrm{Prob}\left\{\sup_{K,M,S}\left|\langle J(K,M,S)\rangle - J_{emp}(K,M,S)\right| \geq \mu\right\} \leq g(P,\mu)$$

$$\lim_{P\to\infty} g(P,\mu) = 0$$

Optimal Truncation

- Gulf of Mexico, Monterey Bay, Louisiana-Texas Shelf, Tropical Atlantic
- $K_{opt} = 40$, $M_{opt} = 30$

Determination of Spectral Coefficients (Ill-Posed Algebraic Equation)

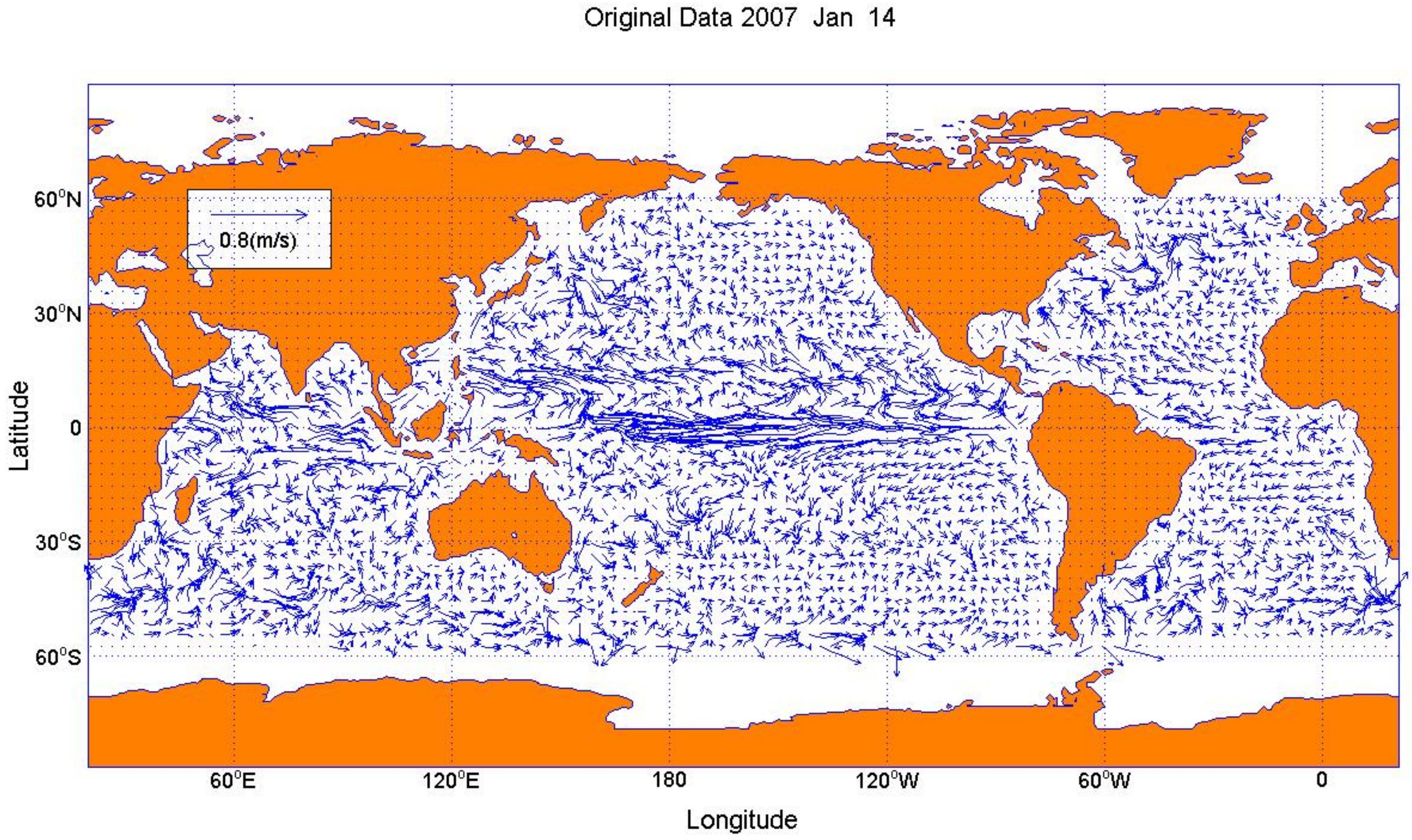
$$\mathbf{A}\hat{\mathbf{a}} = \mathbf{Q}\mathbf{Y},$$

Rotation Method (Chu et al., 2004)

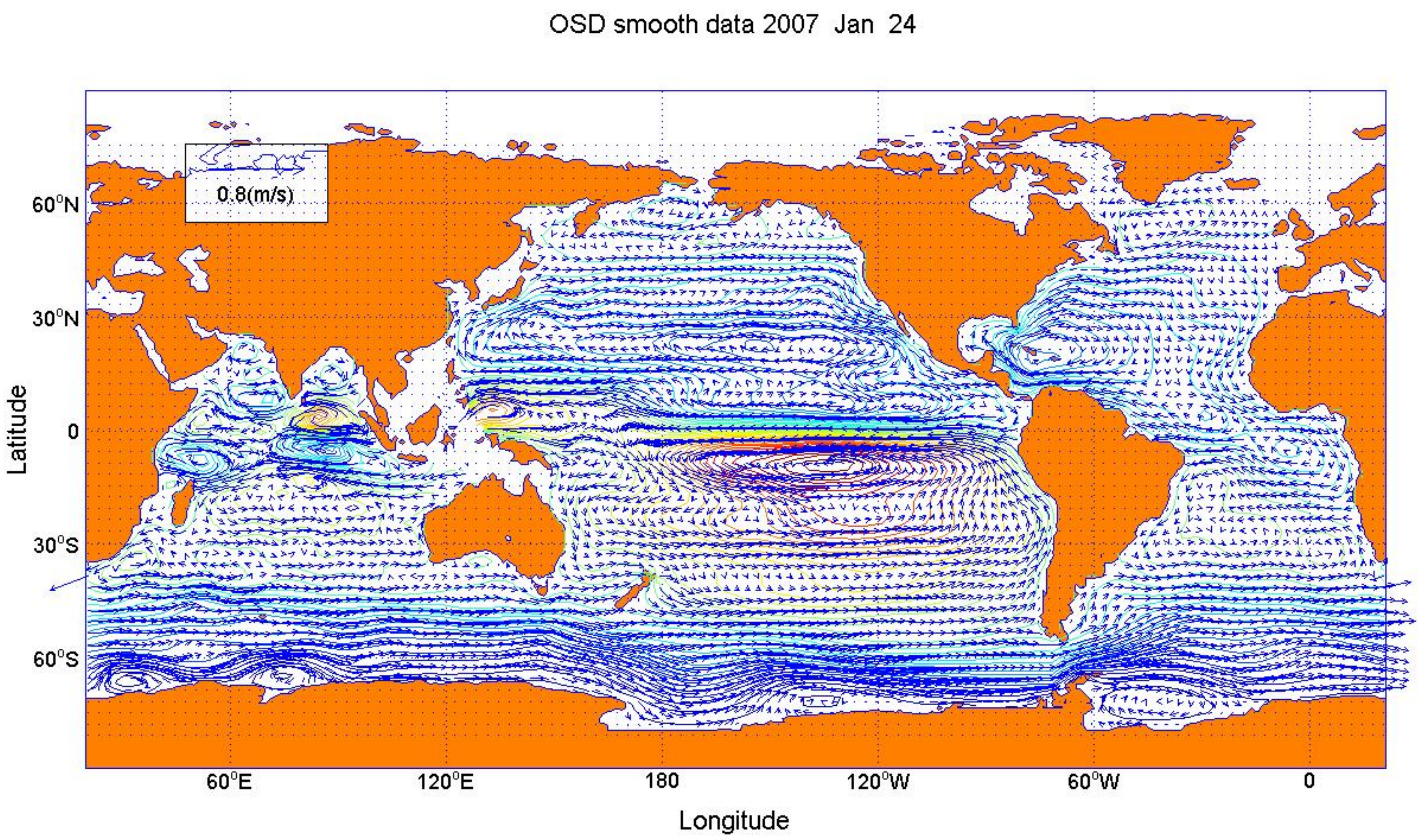
$$\mathbf{SA}\hat{\mathbf{a}} = \mathbf{SQY},$$

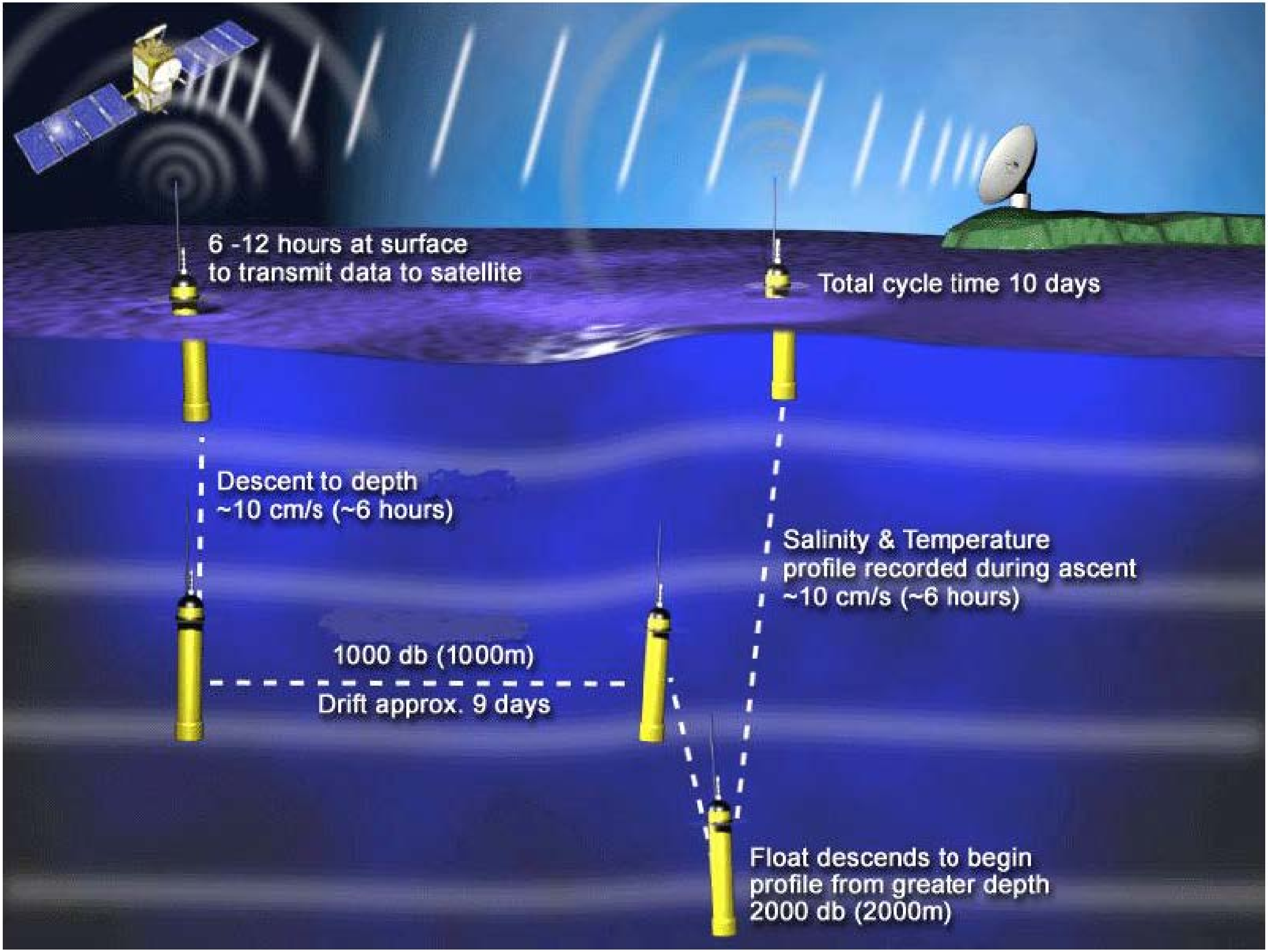
$$J_1 = \|\mathbf{A}\|^2 - \frac{\|\mathbf{SQY}\|^2}{\|\mathbf{a}\|^2} \rightarrow \max,$$

Near-realtime ocean surface currents derived from satellite altimeter and scatterometer data
NOAA OSCAR Data: http://www.oscar.noaa.gov/



OSD on OSCAR Data

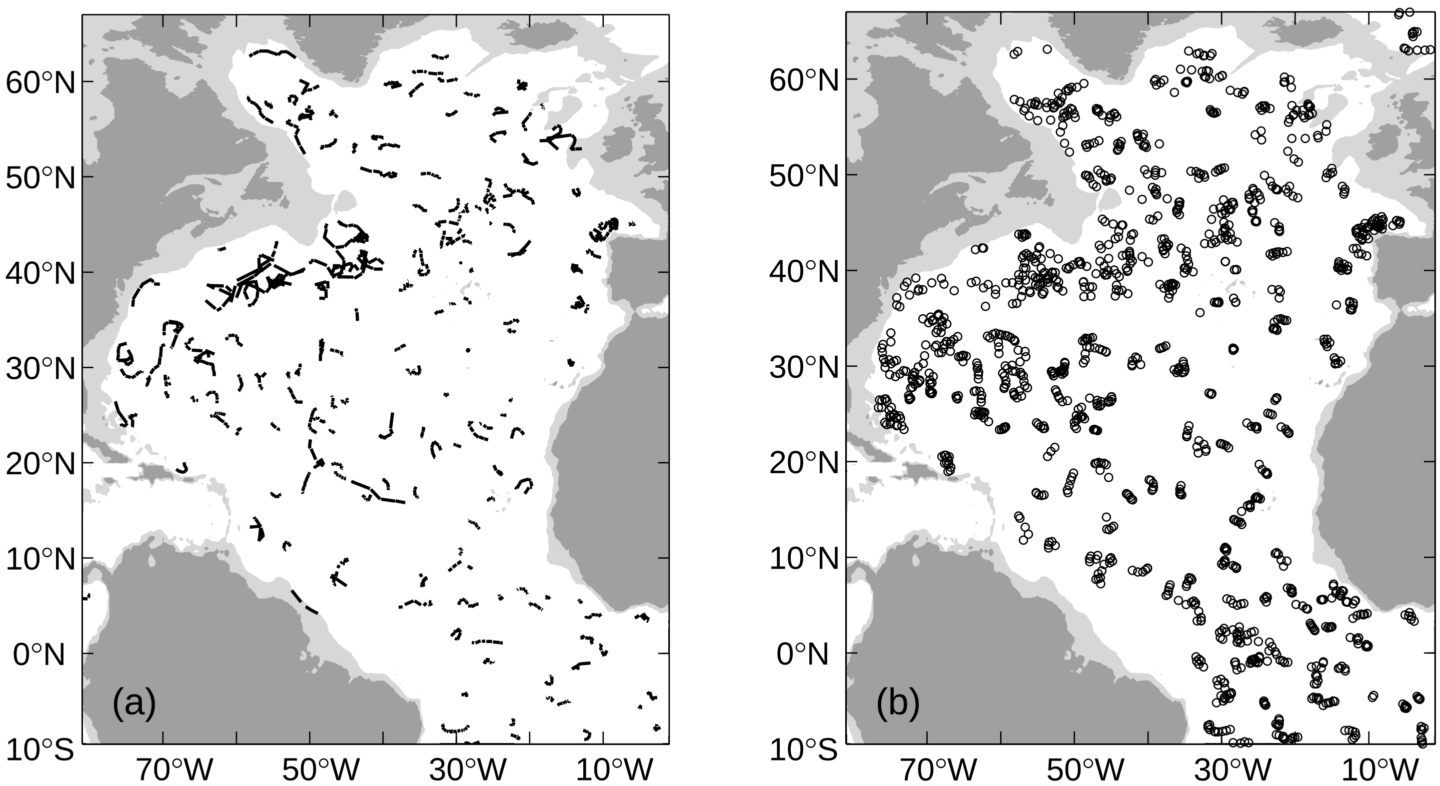



6 -12 hours at surface
to transmit data to satellite
Total cycle time 10 days
Descent to depth
~10 cm/s (~6 hours)
Salinity & Temperature
profile recorded during ascent
~10 cm/s (~6 hours)
1000 db (1000m)
Drift approx. 9 days
Float descends to begin
profile from greater depth
2000 db (2000m)

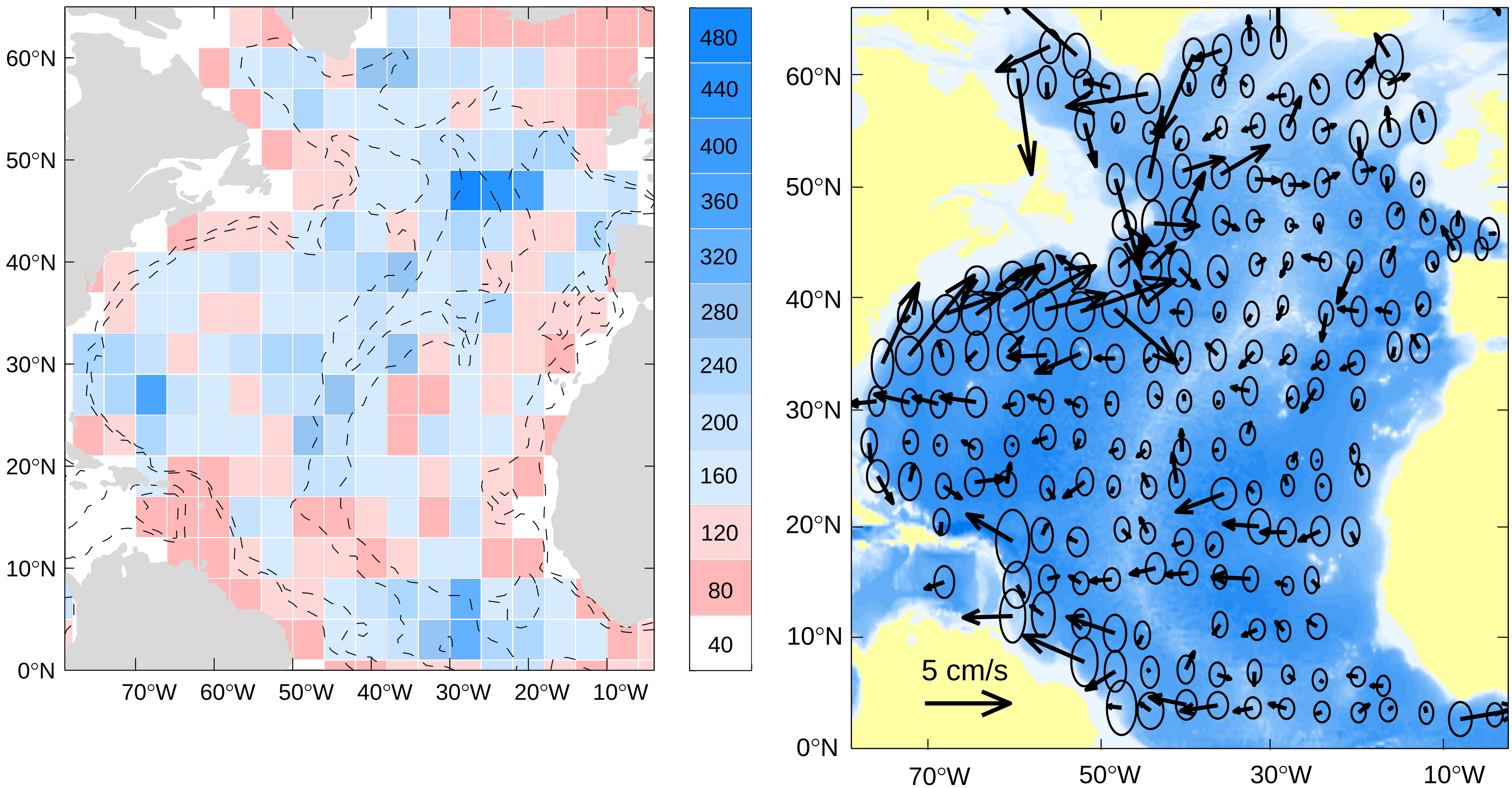
ARGO Observations (Oct-Nov 2004)

(a) Subsurface tracks

(b) Float positions where (T,S) were measured

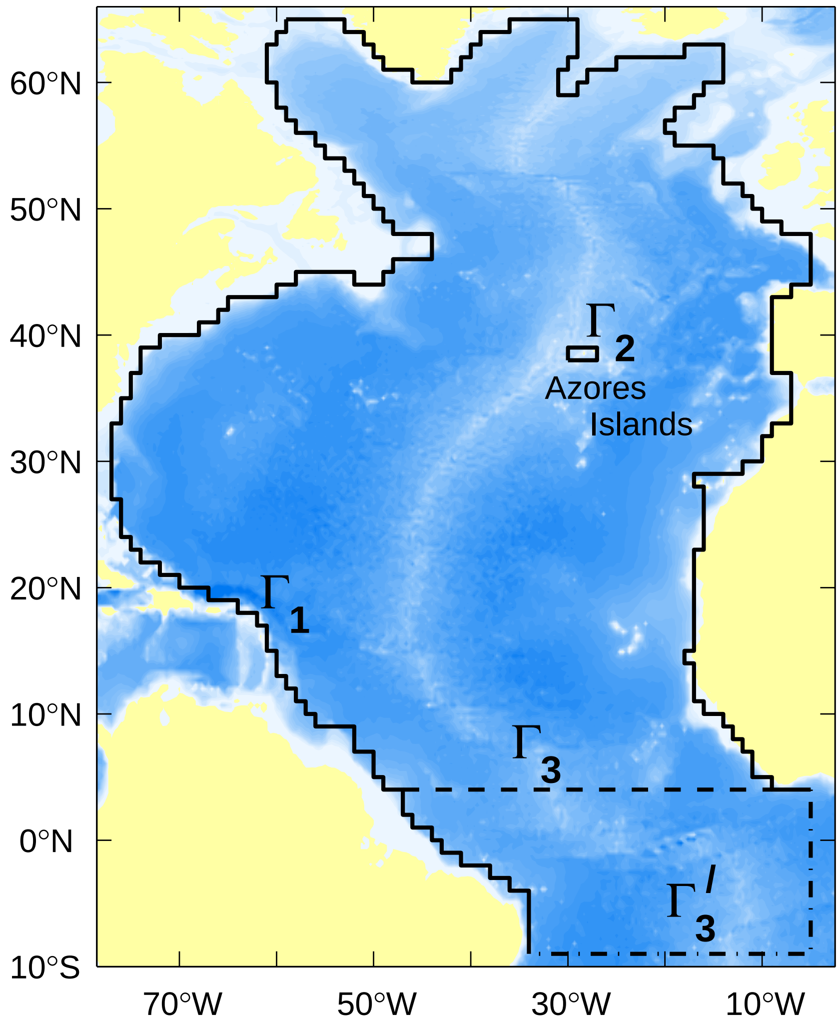


Circulations at 1000 m estimated from the original ARGO float tracks (bin method)
April 2004 – April 2005

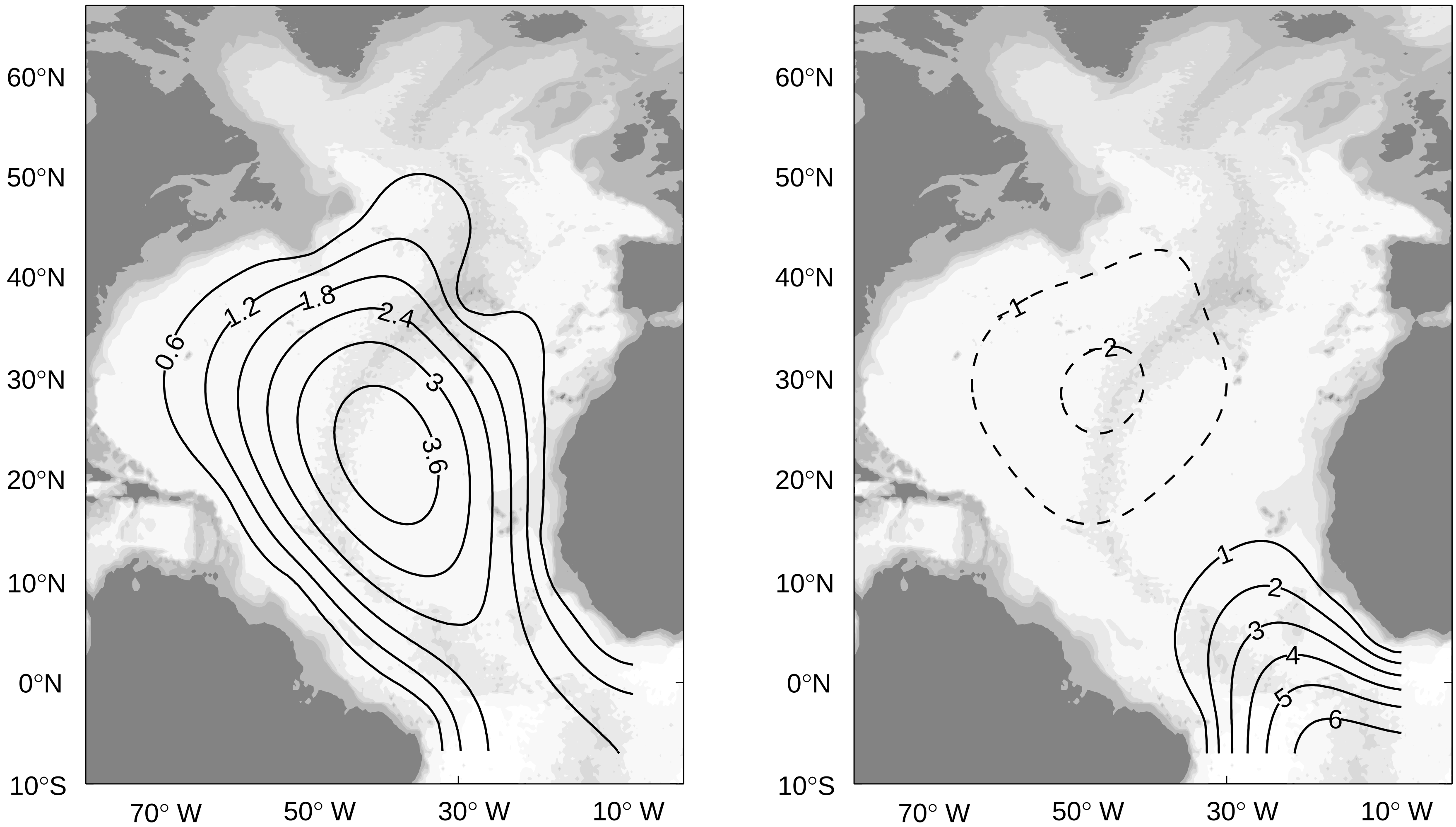


It is difficult to use such noisy data into ocean numerical models.

Boundary Configuration → Basis Functions for OSD

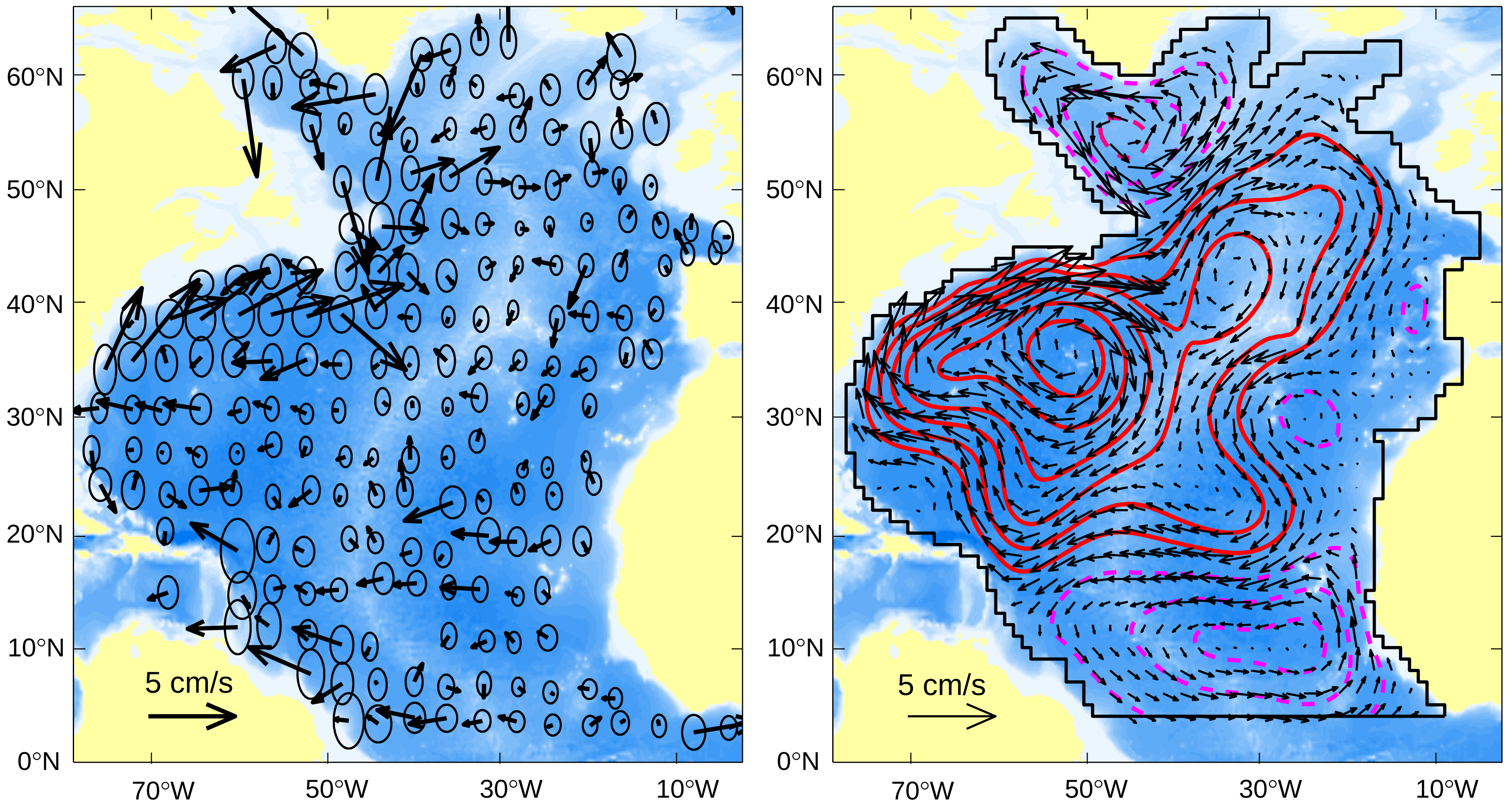


Basis Functions for Streamfunction Mode-1 and Mode-2

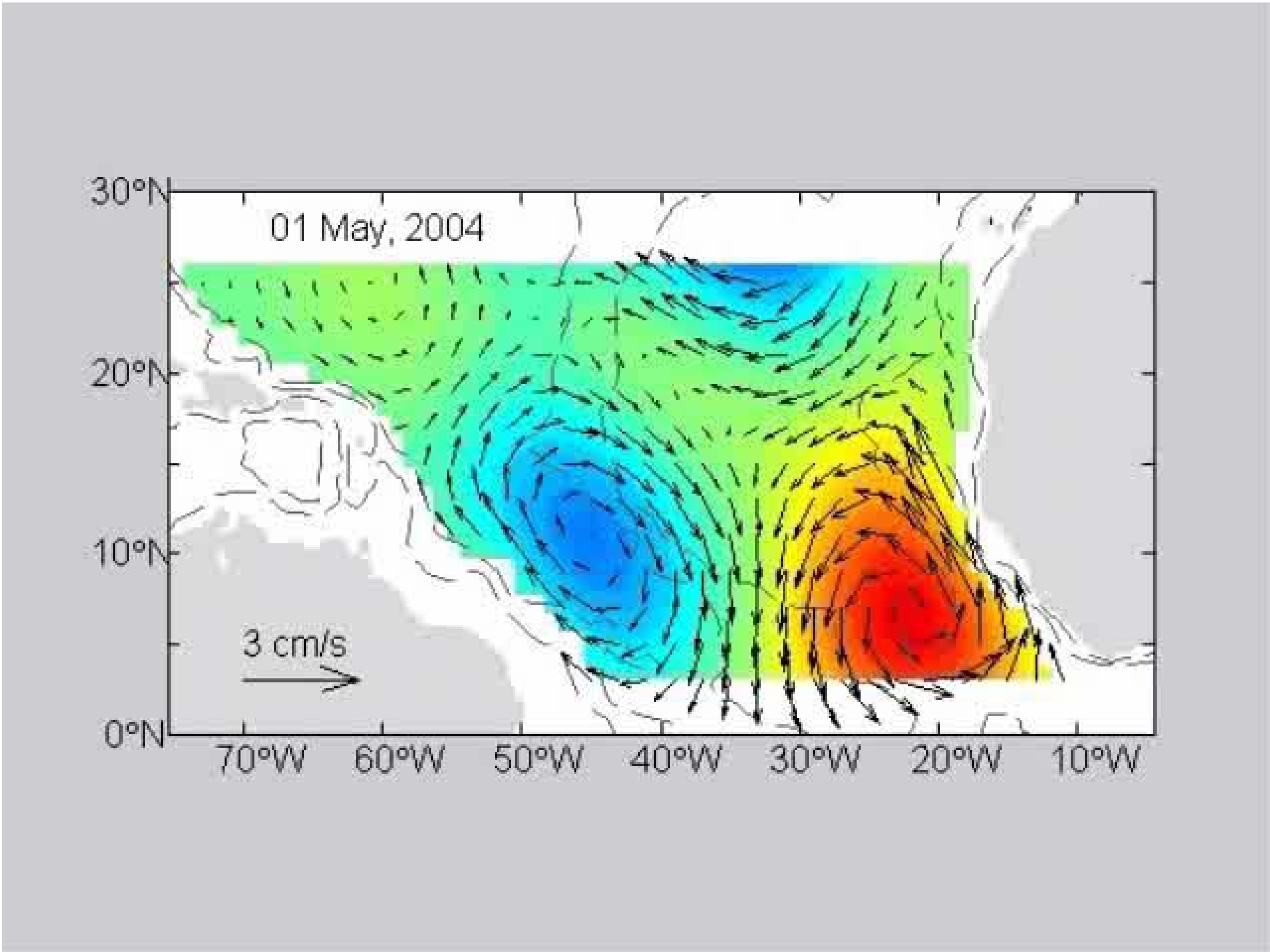


Circulations at 1000 m (March 04 to May 05)

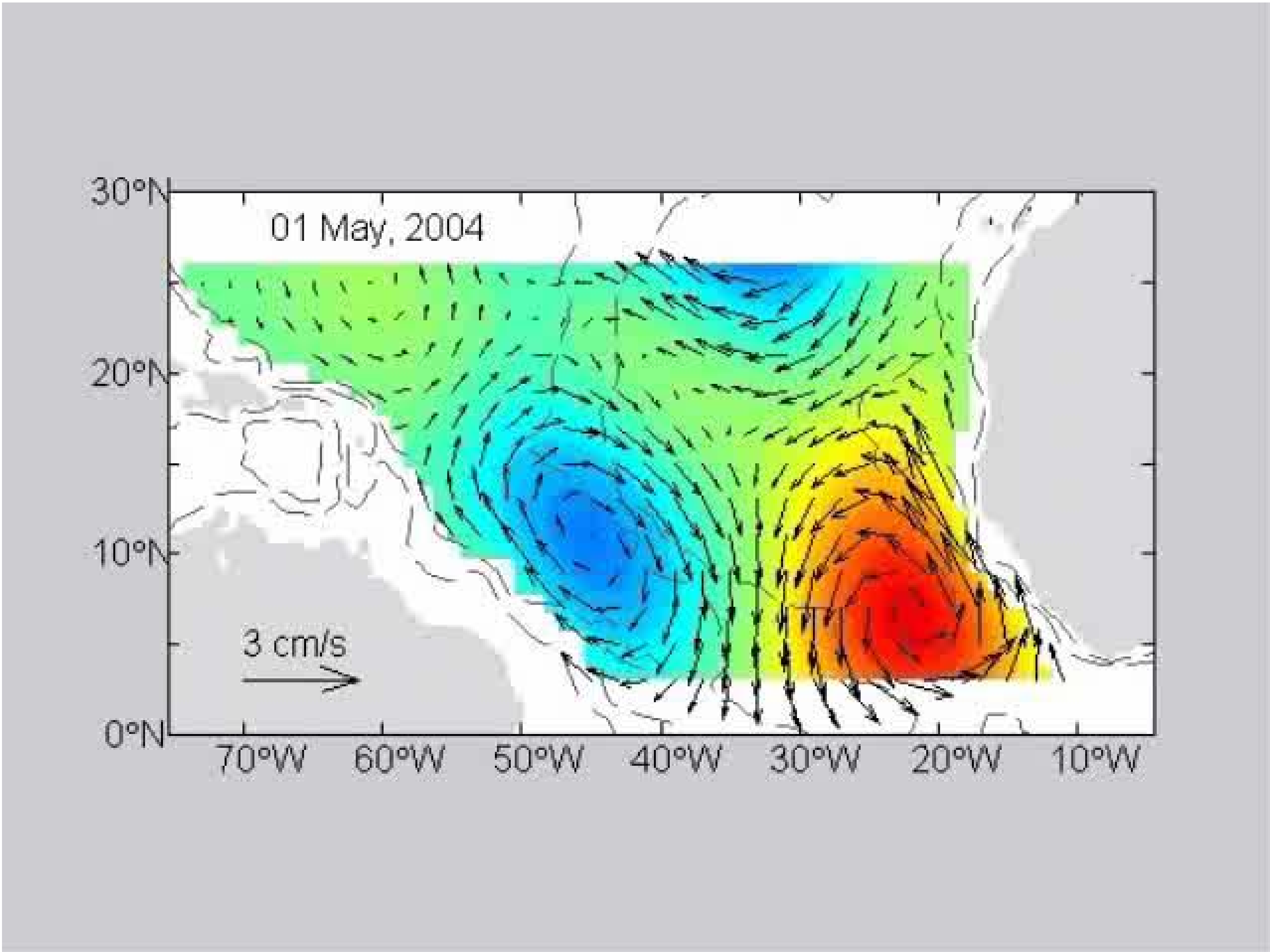
Bin Method OSD



Annual Component

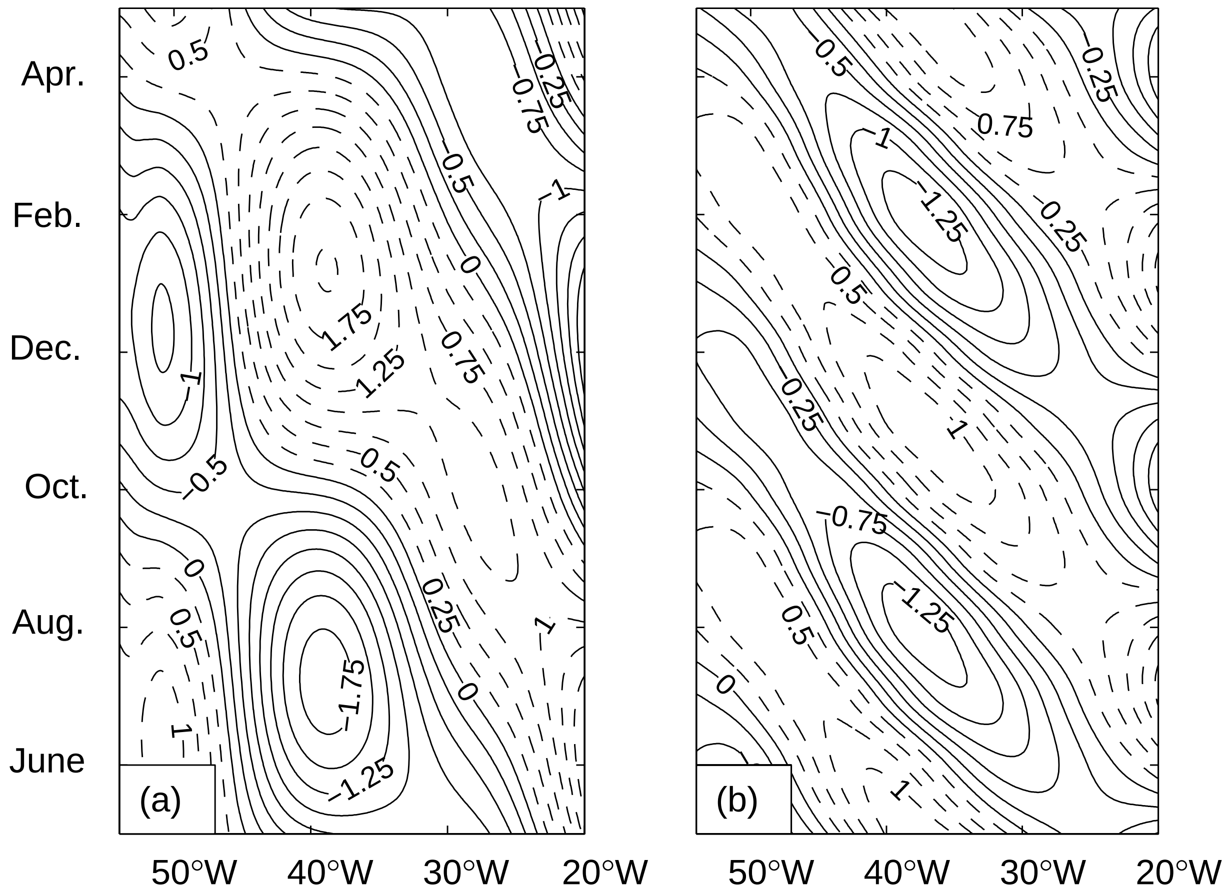


Semi-annual Component



Time –Longitude Diagrams of Meridional Velocity

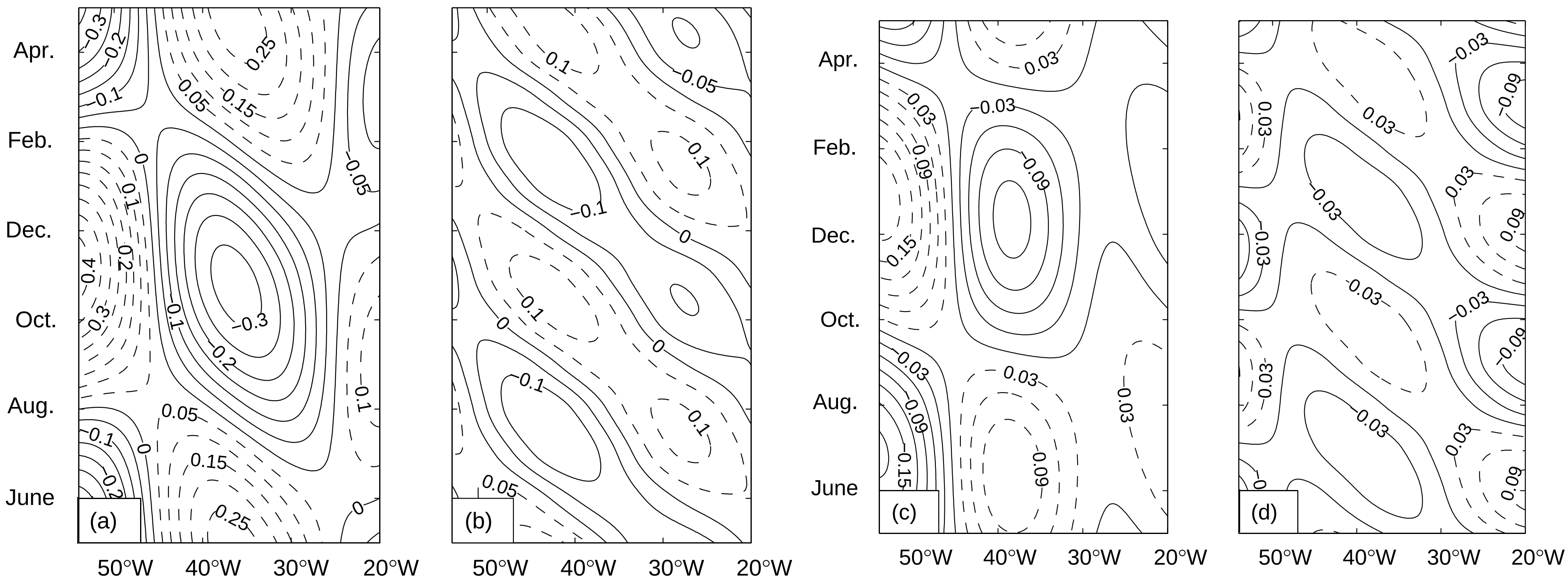
Along 11°N



Annual

Semi-Annual

Time –Longitude Diagrams of temperature Along 11°N



Annual　　Semi-Annual　　Annual　　Semi-Annual

550 m　　950 m

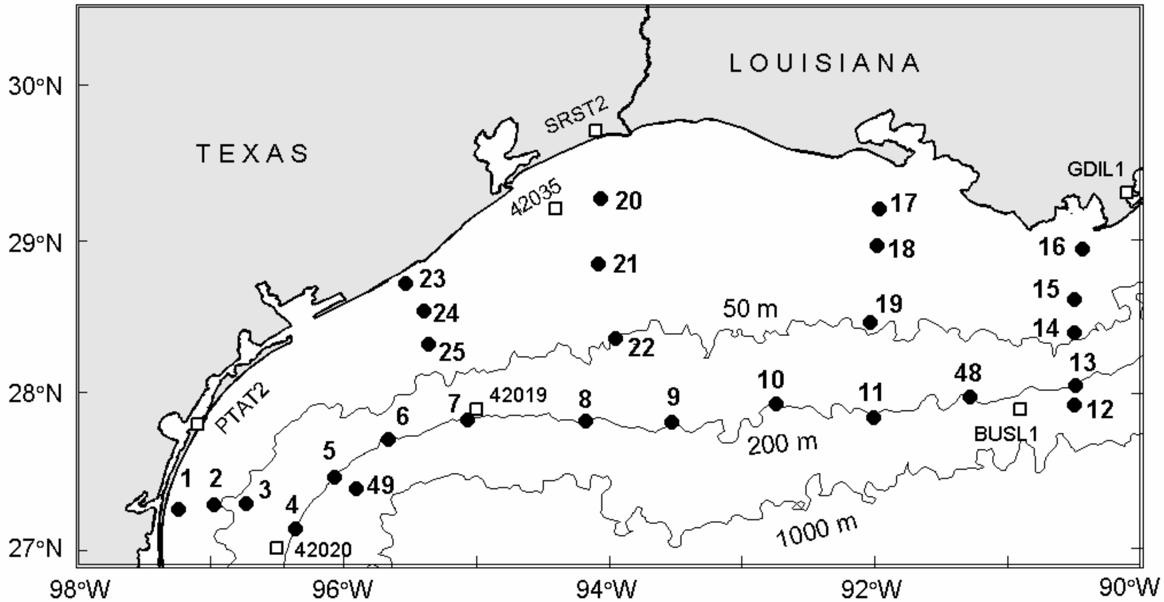
OSD for Analyzing Combined Current Meter and Surface Drifting Buoy Data

Ocean Velocity Observation

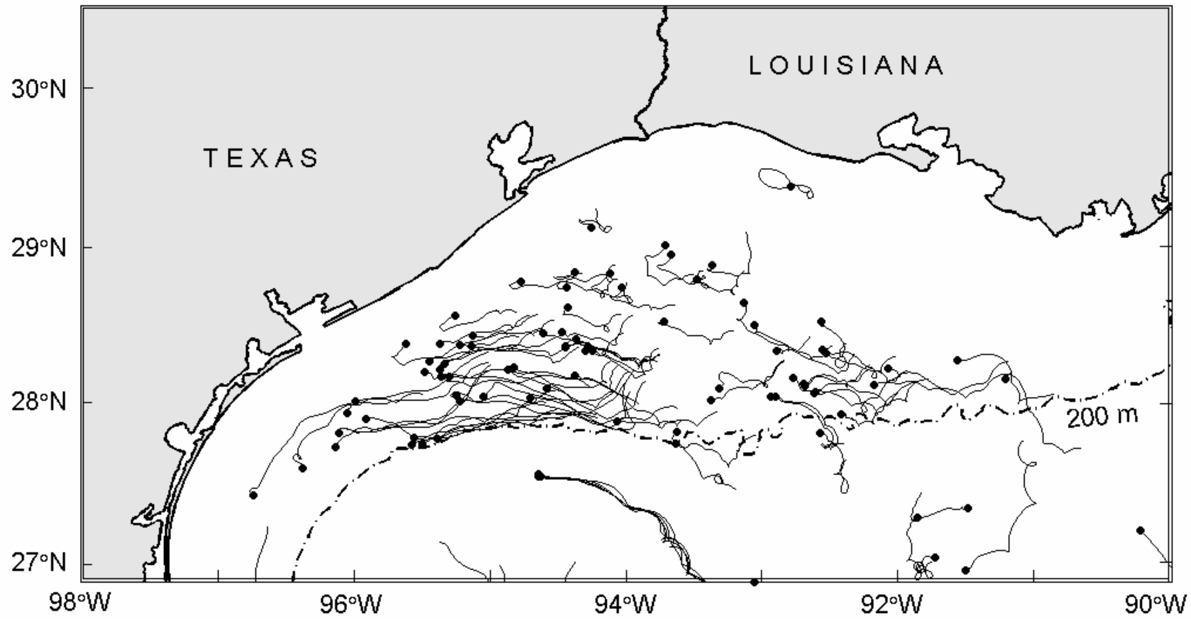
- 31 near-surface (10-14 m) current meter moorings during LATEX from April 1992 to November 1994

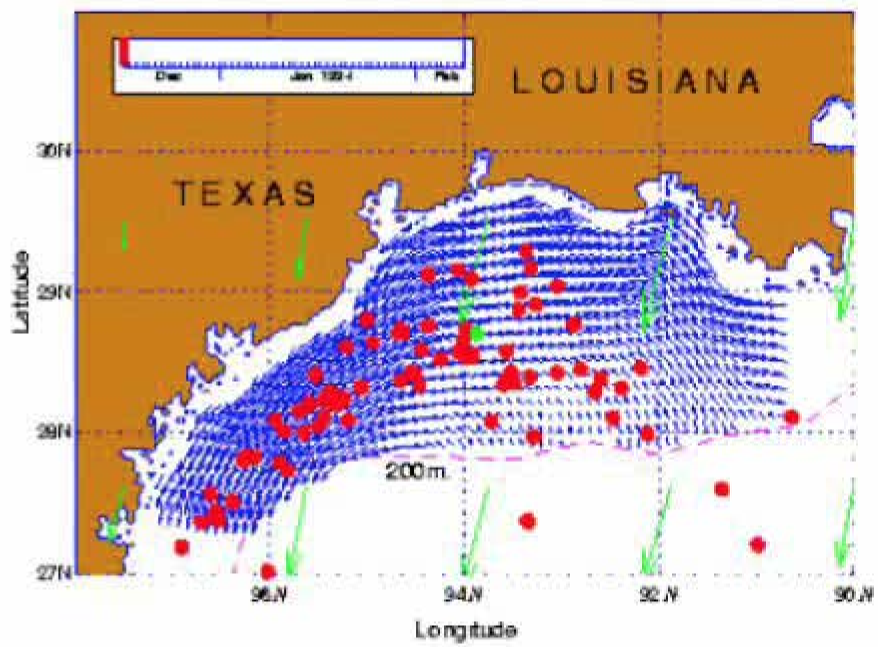
- Drifting buoys deployed at the first segment of the Surface Current and Lagrangian-drift Program (SCULP-I) from October 1993 to July 1994.

Moorings and Buoys



LTCS current reversal detected from SCULP-I drift trajectories.





Dec
Jan 1994
Feb
LOUISIANA
TEXAS
30N
29N
28N
27N
200m
96W
94W
92W
90W
Latitude
Longitude

Conclusions

- (1) Data analysis is important for coastal modeling and prediction.
- (2) KZ filter reduces model-data incompatibility.
- (3) OSD is an effective method for establishing gidded data from sparse and noisy ocean observations.